Land Surface Modeling and Data Assimilation

http://lis.gsfc.nasa.gov

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Key processes of the water cycle

Transformation of water from liquid to gas phase

Transpiration: water taken up by the plants released to the atmosphere

Difficult to separate the processes of evaporation and transpiration; often called evapotranspiration

Water escapes through the stomata (small pores on the leaves). Plants regulate the rate of transpiration by controlling the size of stomata

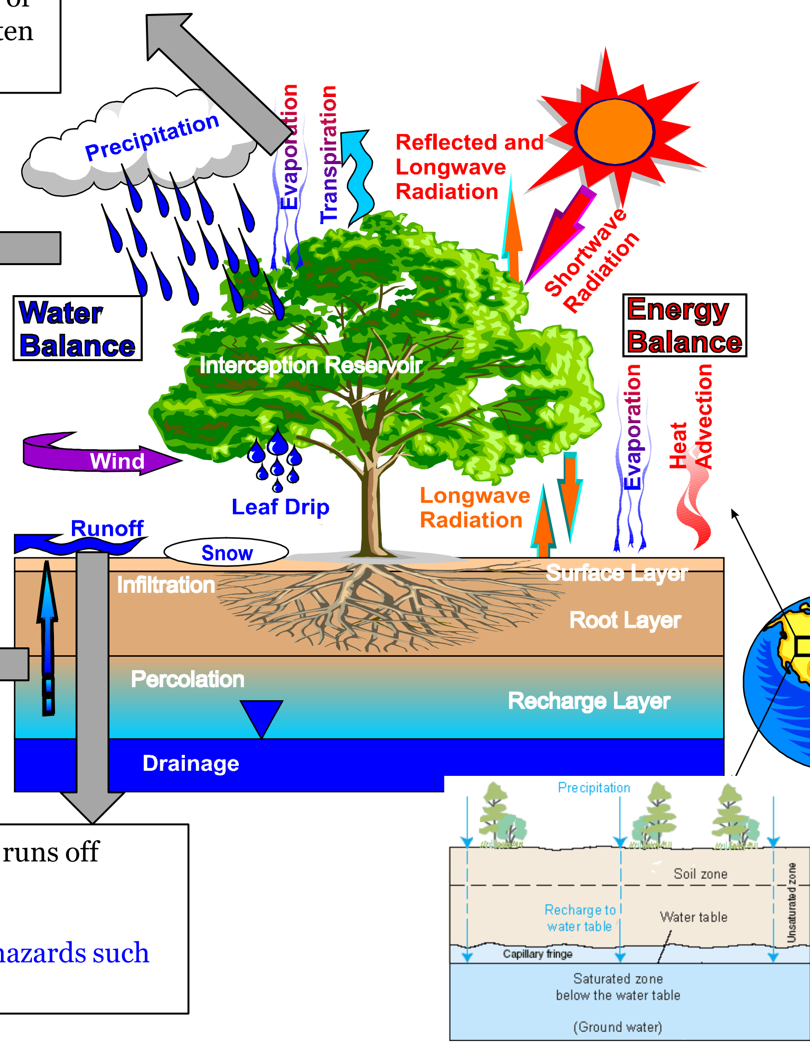
Under water stress conditions, plants would close the stomata to conserve energy

Soil moisture: Variable representing reservoir of water on land; controls the exchanges of water and energy between the land and atmosphere; affects evapotranspiration, runoff, infiltration.

Soil moisture levels are related to water resource applications; plant growth, water stress, droughts, floods

Different forms of precipitation: Rain, snow, hail, fog, drip, graupel, sleet

Many of the water related problems are related to the fact that precipitation is not evenly distributed in space and time



Snow: Another variable representing reservoir of water on land; intimately affects runoff, infiltration.

In many mid-latitude and high-altitude regions, the seasonal water storage and associated spring melt dominate the local hydrology.

Infiltration: Some of the precipitation on land seeps into the ground to be stored in aquifers, transported to lakes and streams through subsurface flow

Runoff: Water that does not infiltrate the soil runs off across the surface into streams, rivers, lakes.

Runoff and infiltration contribute to natural hazards such as floods

Groundwater/aquifer: water stored in the saturated zone. The top of the aquifer is called water table

Groundwater accounts for almost 33% of total water withdrawals worldwide; Key as a strategic reserve in times of drought; often ignored in management decisions.

Challenges of water cycle monitoring

Technique	Advantages	Disadvantages
In-situ measurements	"Real" data	Labor intensive; quality control issues; spatial interpolation
Remote sensing	Spatial coverage	Resolution; Sensing limitations; retrieval errors
Numerical model	Choose any region or time period; Economical	Quality limited by input; difficulty representing complex processes

Land Surface Observations: in-situ

Precipitation: Surface Gages and Doppler Radar

Radiation: DOE-ARM, Mesonets, USDA-ARS

Surface Temperature: DOE-ARM, Mesonets, NWS-ASOS,

Soil Moisture: DOE-ARM, Mesonets, Global Soil Moisture Data Bank, USDA-ARS

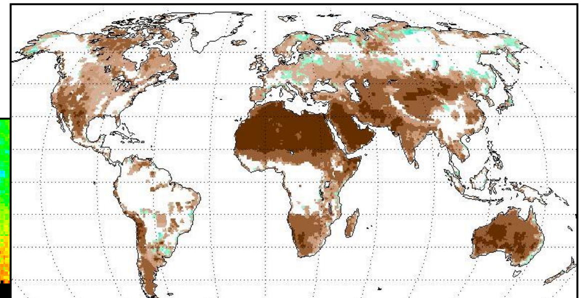
Groundwater: Well Observations

Snow Cover, Depth & Water: Field Experiments, SNOTEL

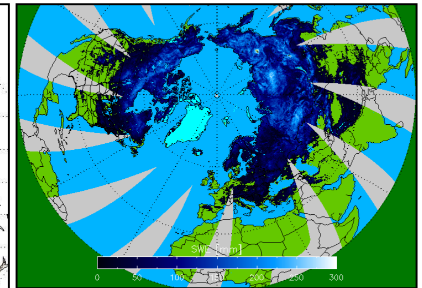
Streamflow: Real-Time Stream Gauge

Vegetation: Field Experiments

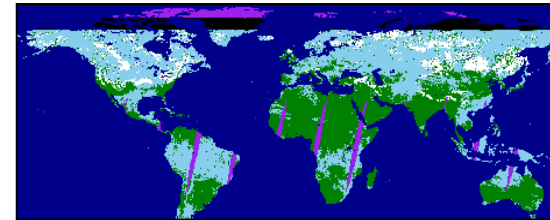
Soils: Field Experiments



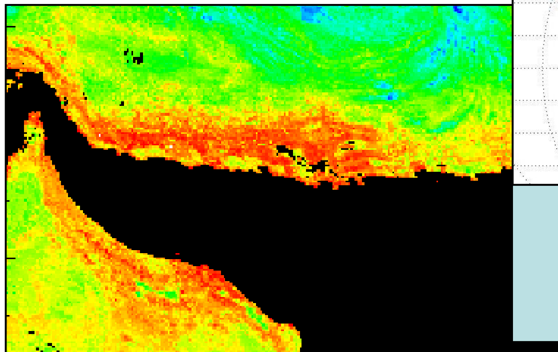
Surface soil moisture
(SMMR, TRMM, AMSR-E,
SMOS, Aquarius, SMAP)



Snow water equivalent
(AMSR-E, SSM/I,
SCLP)

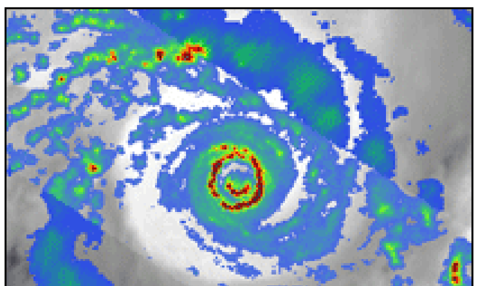


Snow cover fraction
(MODIS, *VIIRS, MIS*)

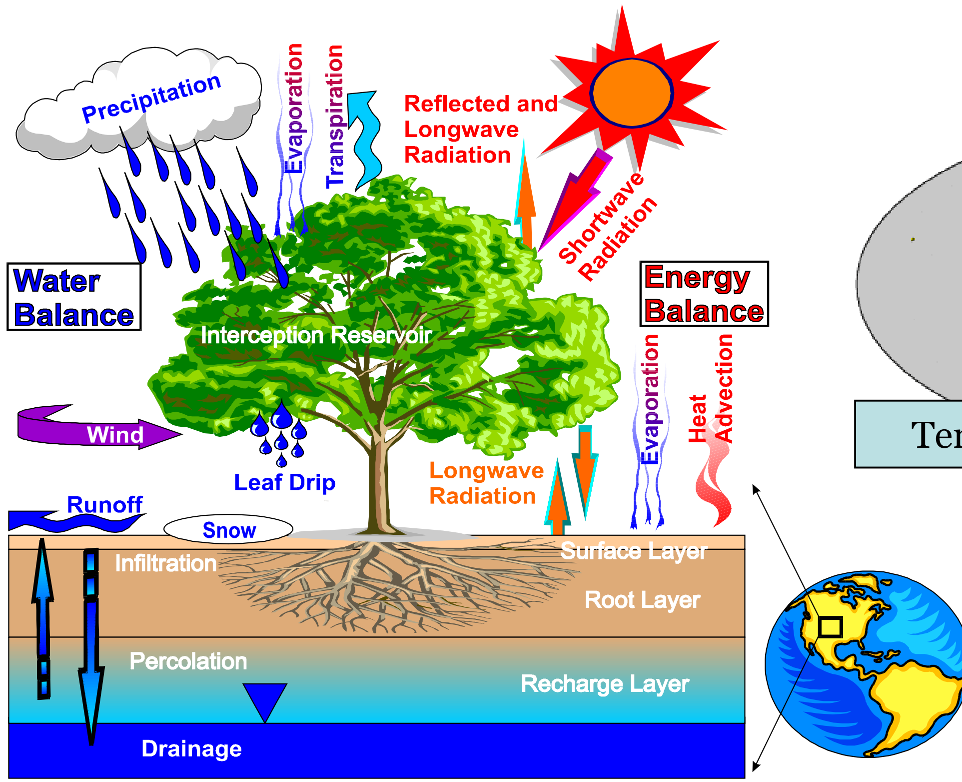


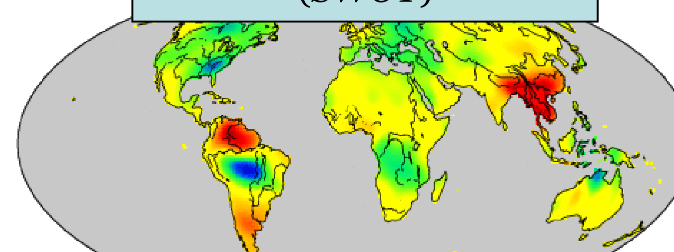
Land surface temperature
(MODIS, AVHRR,GOES,...)

Water surface elevation
(*SWOT*)

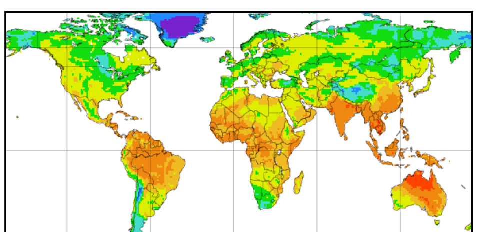


Precipitation
(TRMM, *GPM*)





Terrestrial water storage (GRACE)

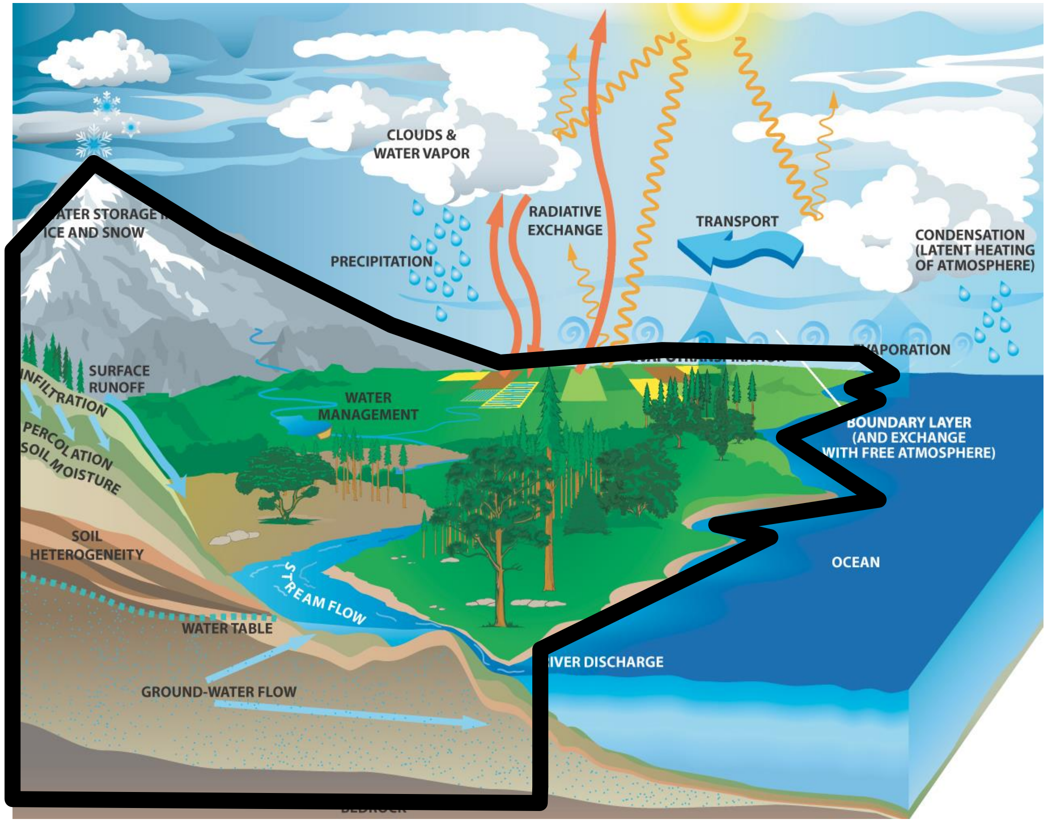


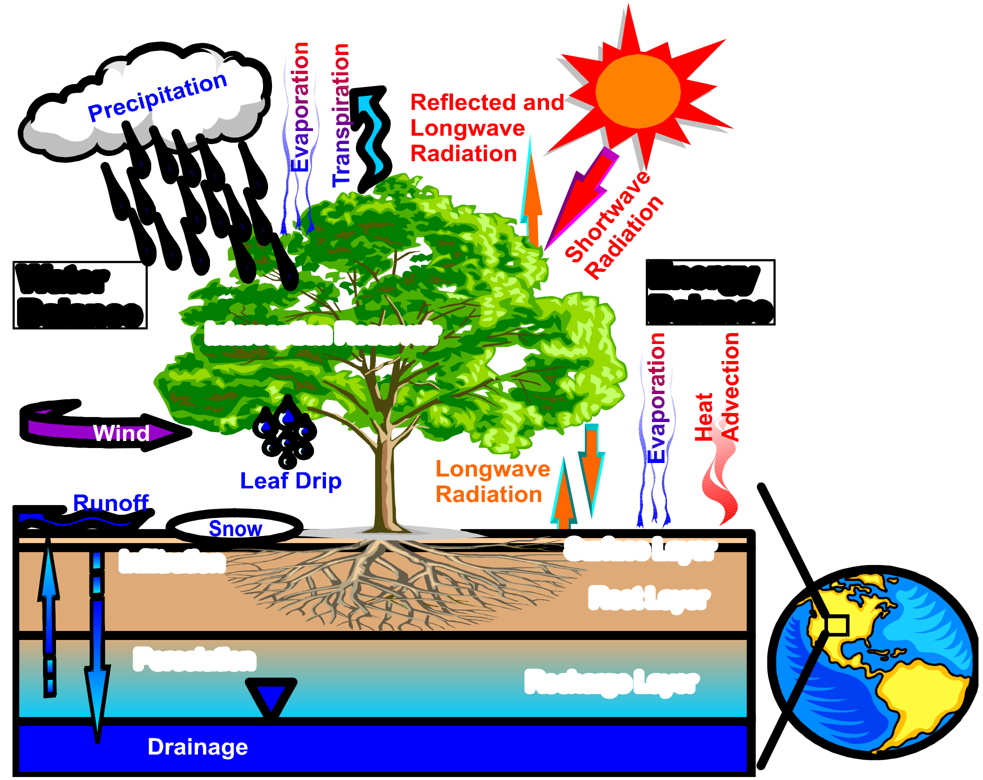
Radiation
(CERES, *CLARREO*)

Vegetation/Carbon
(AVHRR, MODIS, *DESDynI,
ICESat-II, HyspIRI, LIST,
ASCENDS*)

Satellite observations

What are "Land surface models"?





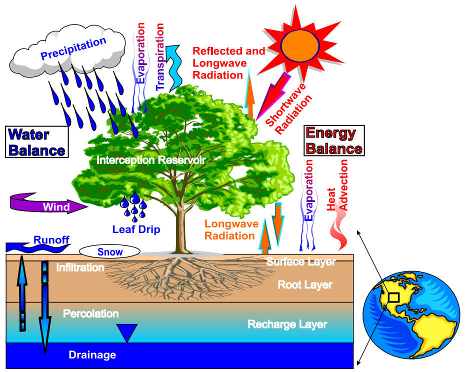
Land surface models solve for the interaction of energy, momentum and mass between the surface and the atmosphere

$$R_n = \lambda E + SH + G \qquad \frac{dS}{dt} = P - E - R$$

Estimates fluxes, land conditions (soil moisture, snow, runoff, ...)

e.g. : Noah, CLM, VIC, Catchment, JULES ...

How do we combine the information from satellite observations and models?



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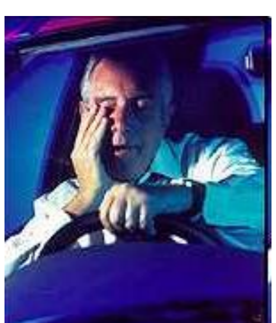
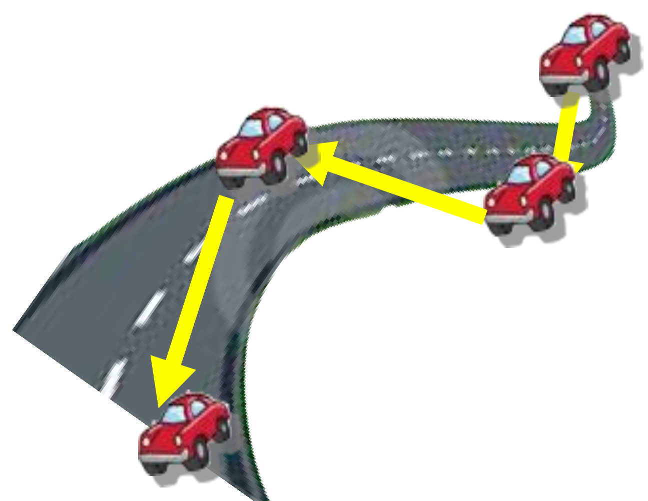
Models **Observations**

Data assimilation is the method used to incorporate observational data into model forecasts

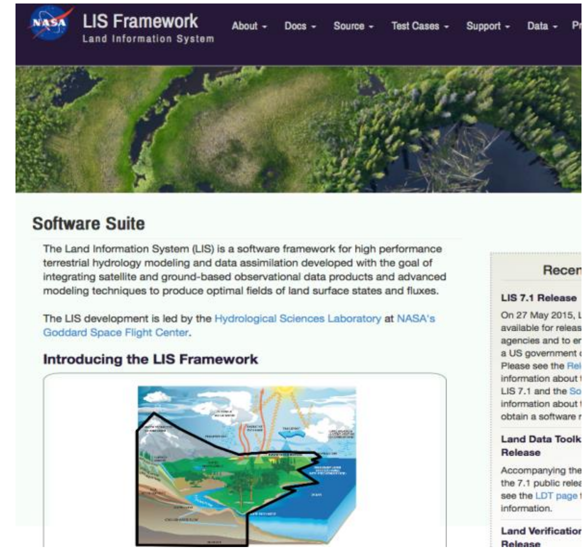


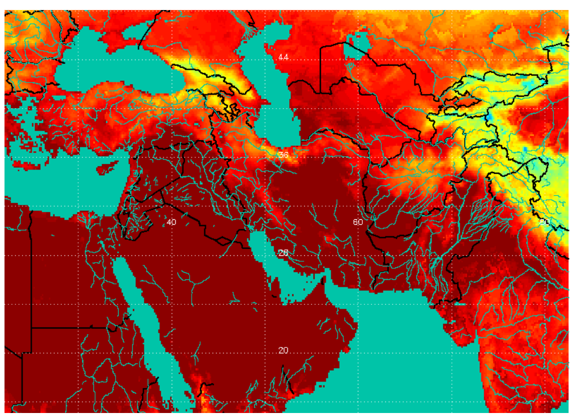
Like a "sleepy-driver" scenario

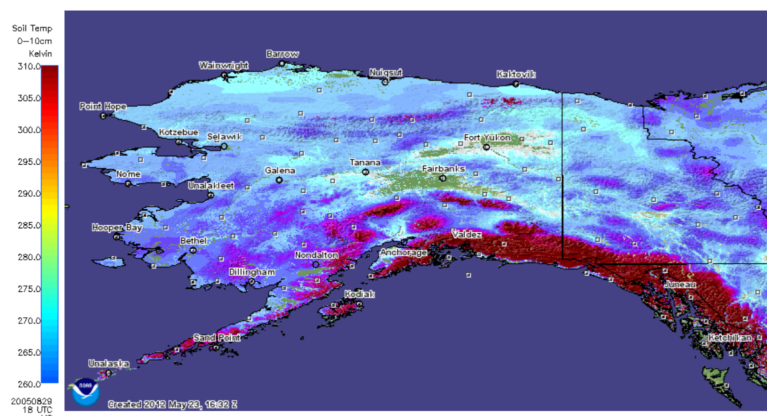


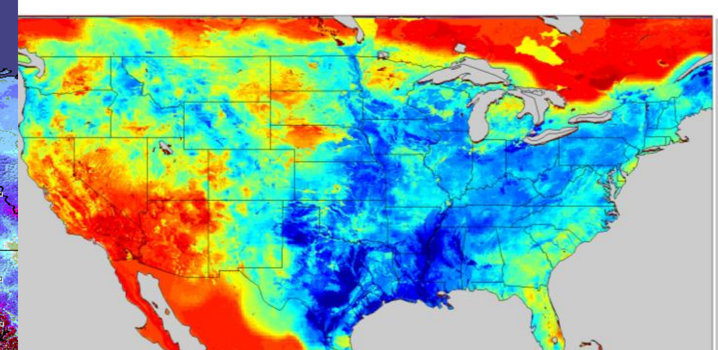
Land Data Assimilation Systems (LDASs)

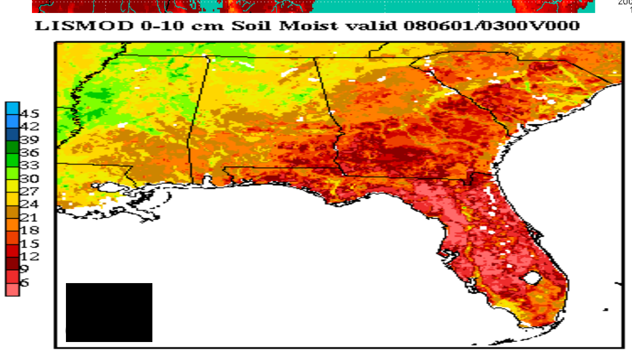
- Philosophy: Use best available observations to inform models
- NASA Land Information System (LIS; http://lis.gsfc.nasa.gov) - infrastructure that enables LDASs
- Used in several US and international agencies, universities for research and applications (Famine early warning, crop forecasts, water resources management, …)

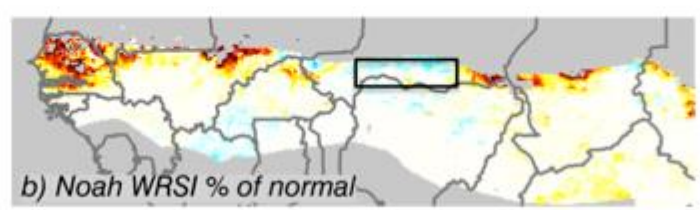


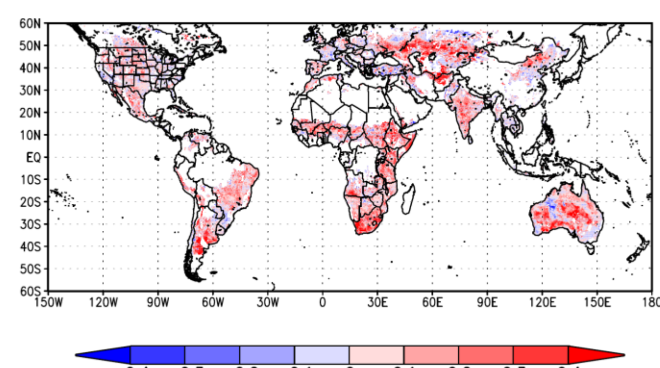






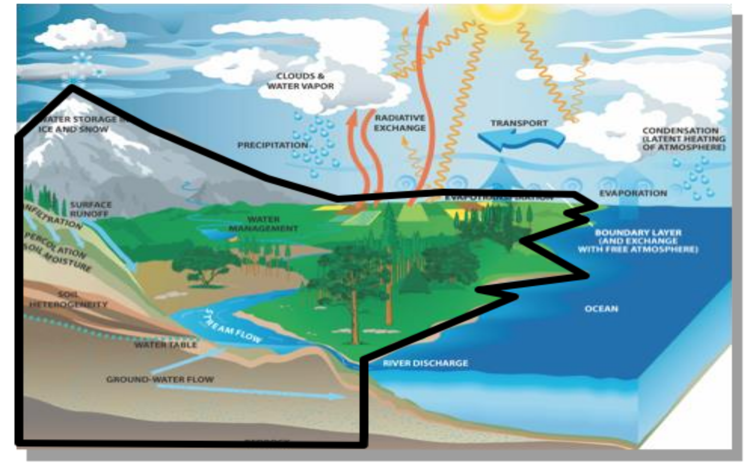




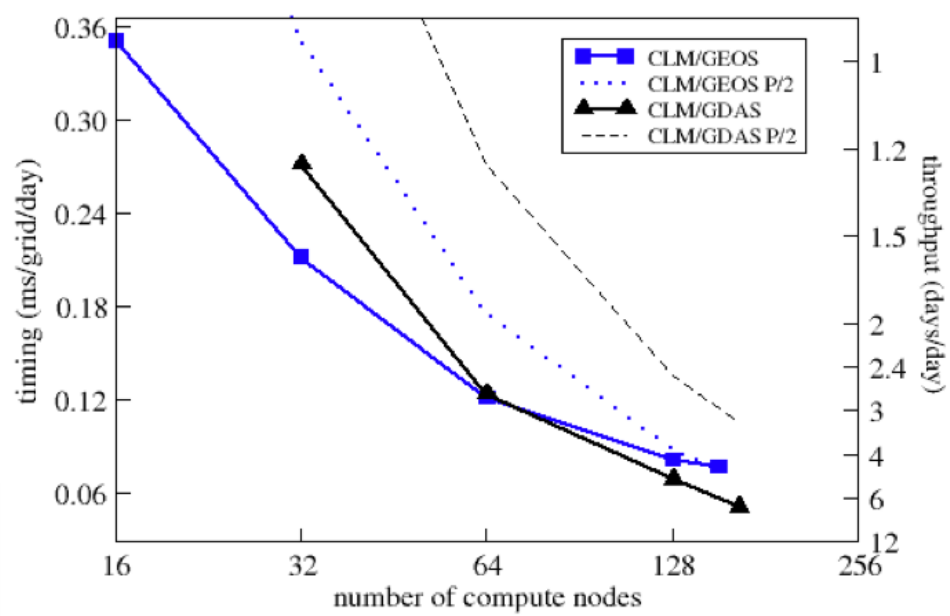


Land Information System (LIS; lis.gsfc.nasa.gov)

- A system to study land surface processes and land-atmosphere interactions
  - “Use best available observations” to constrain and inform models.
- Runs a variety of land surface models
- Integrates satellite, ground and reanalysis data
- Includes high performance support for fine resolution modeling
- Built as a flexible framework that allows the interoperable use of data and models
- Coupled to other Earth system models
- Includes a number of computational subsystems for exploiting information from observations.

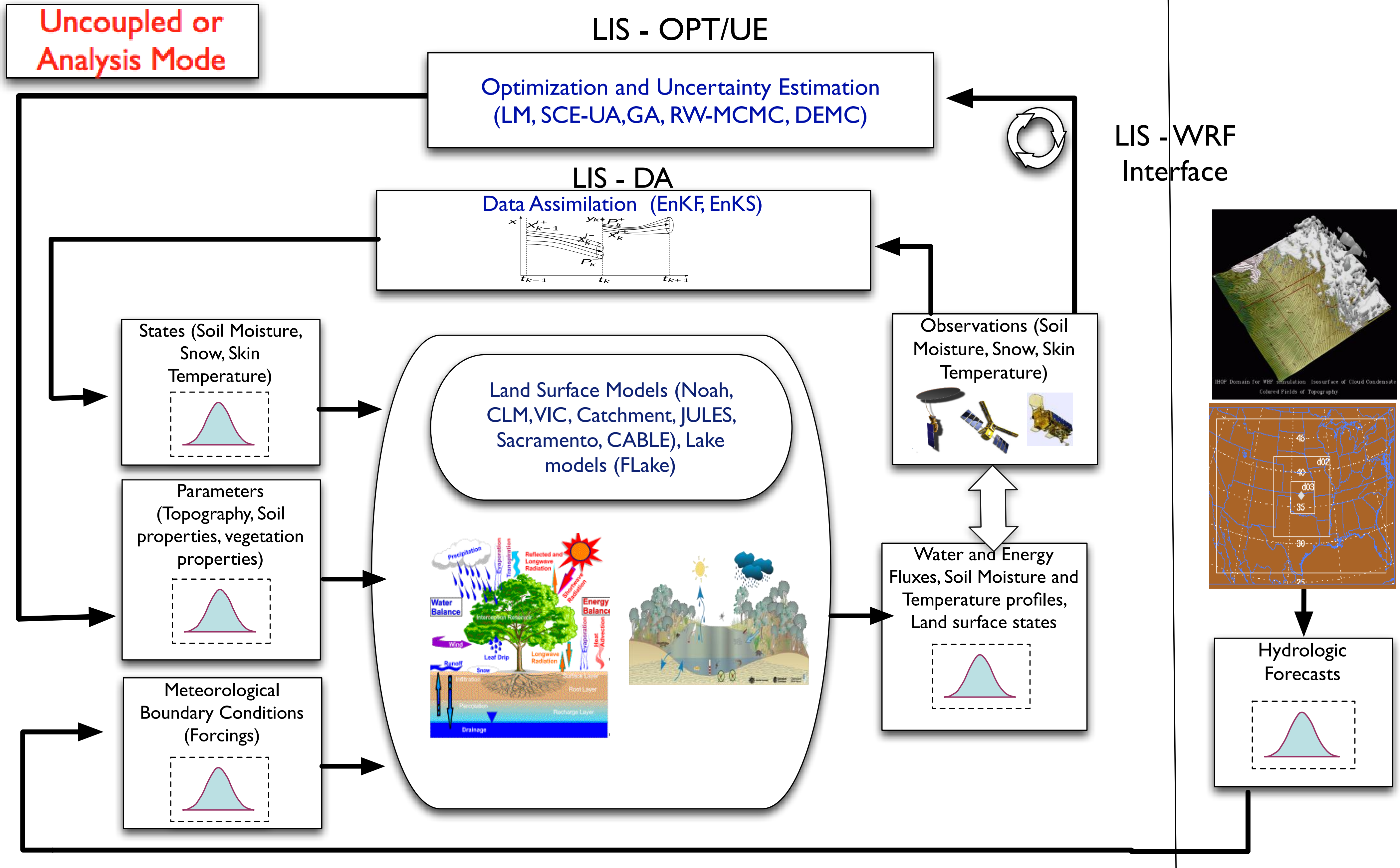


Resolution	¼ deg	1 km
Land Grid Points	2.43E5	1.44E8
Disk Space/day (Gb)	1	700
Memory (Gb)	3	1500



Kumar, S.V., C.D. Peters-Lidard, Y. Tian, P.R. Houser, J.Geiger, S. Olden, L.Lighty,J.L. Eastman, B. Doty, P.Dirmeyer, J. Adams, K. Mitchell, E.F. Wood, J. Sheffield (2006), Land Information System – An Interoperable Framework for Land Surface Modeling, *Environmental Modeling and Software*, 21, 1402—1415.

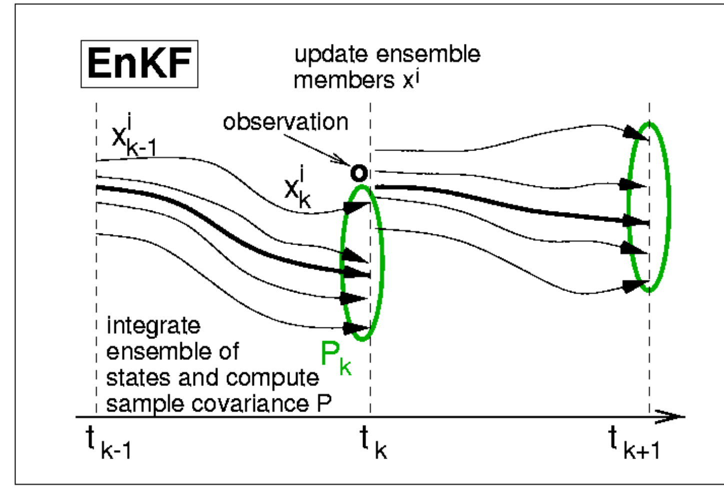
Computational subsystems and coupled models with LIS

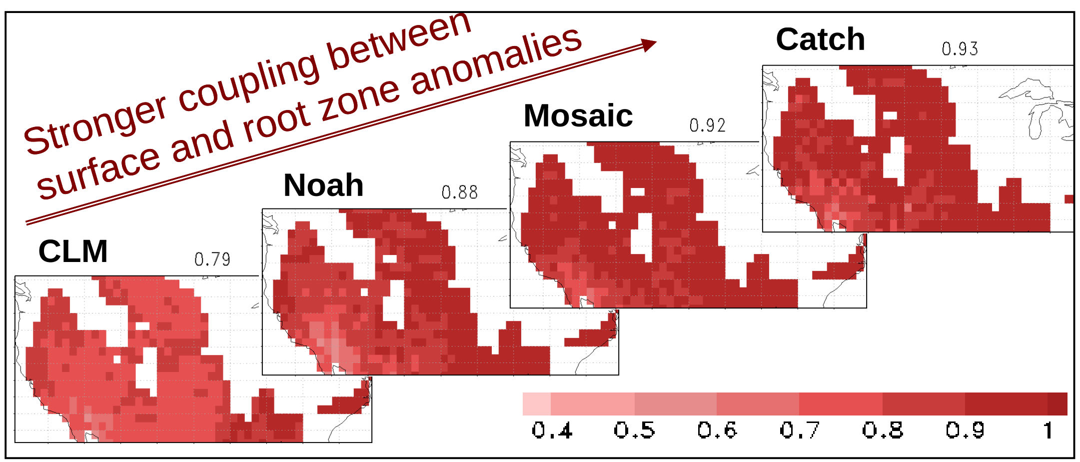


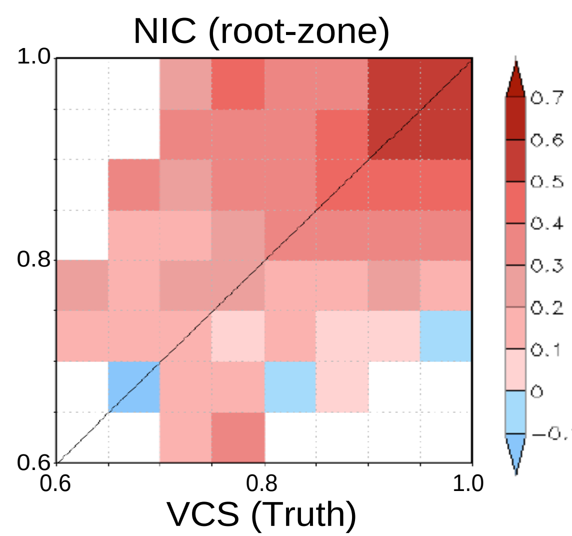
Kumar, S.V., C.D. Peters-Lidard, J.L. Eastman, W.-K. Tao (2007), An integrated High Resolution Hydrometeorological Modeling Testbed using LIS and WRF, *Environmental Modeling and Software*, 23(2), 169-181.

Data Assimilation subsystem in LIS

- Primarily used for state estimation - Corrects model states based on observations
- Advanced algorithms such as the Ensemble Kalman Filter (EnKF), Ensemble Kalman Smoother (EnKS)
- Supports the interoperable use of multiple land surface models, multiple algorithms and multiple observational data sources
- Support for concurrent data assimilation, forward models, radiance assimilation, observation operators employing advanced data fusion methods (deep learning)







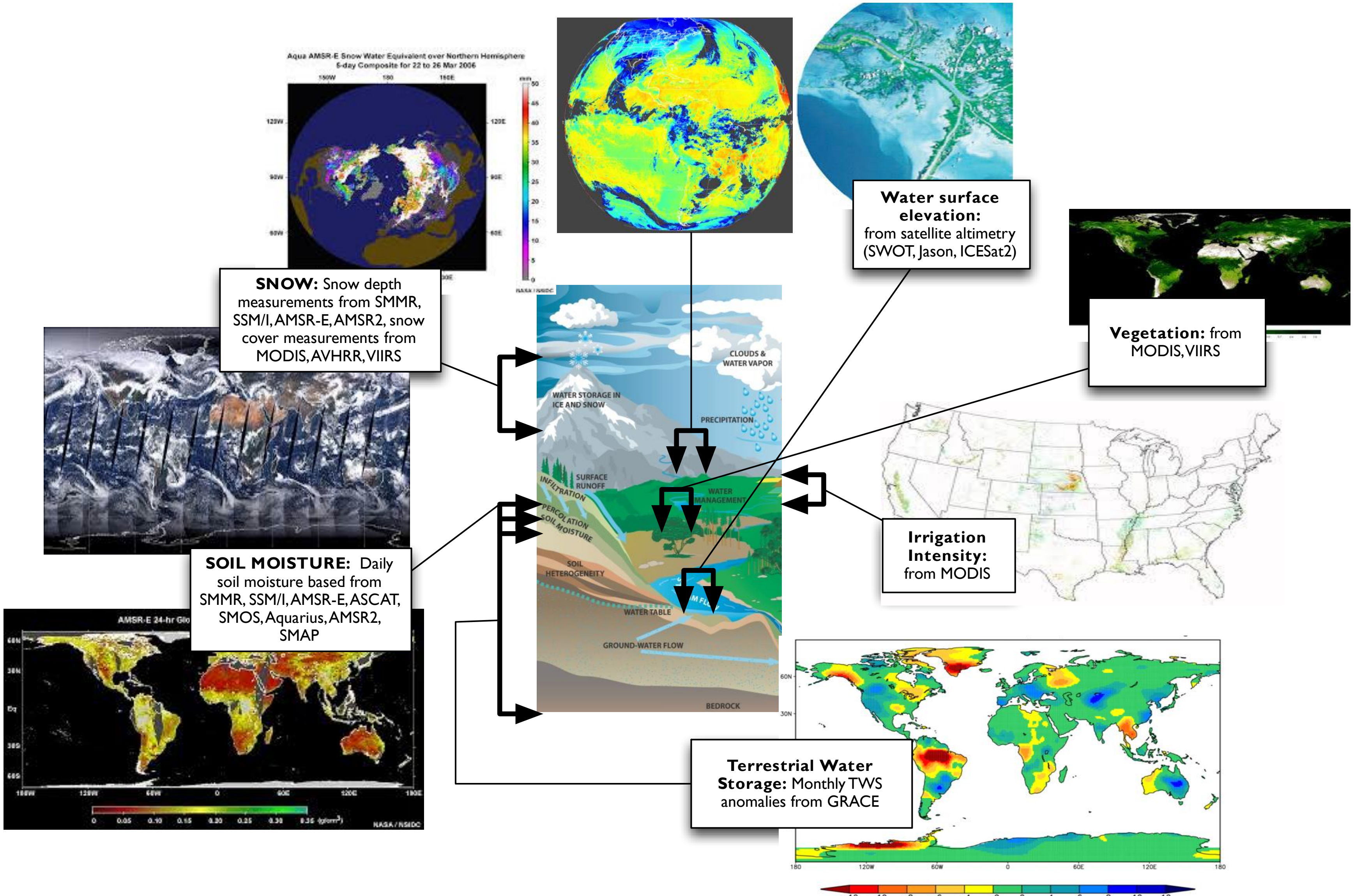
NIC = normalized information contribution

VCS = vertical coupling strength

Stronger coupling between surface and root zone provides more “efficient” assimilation of surface observations.

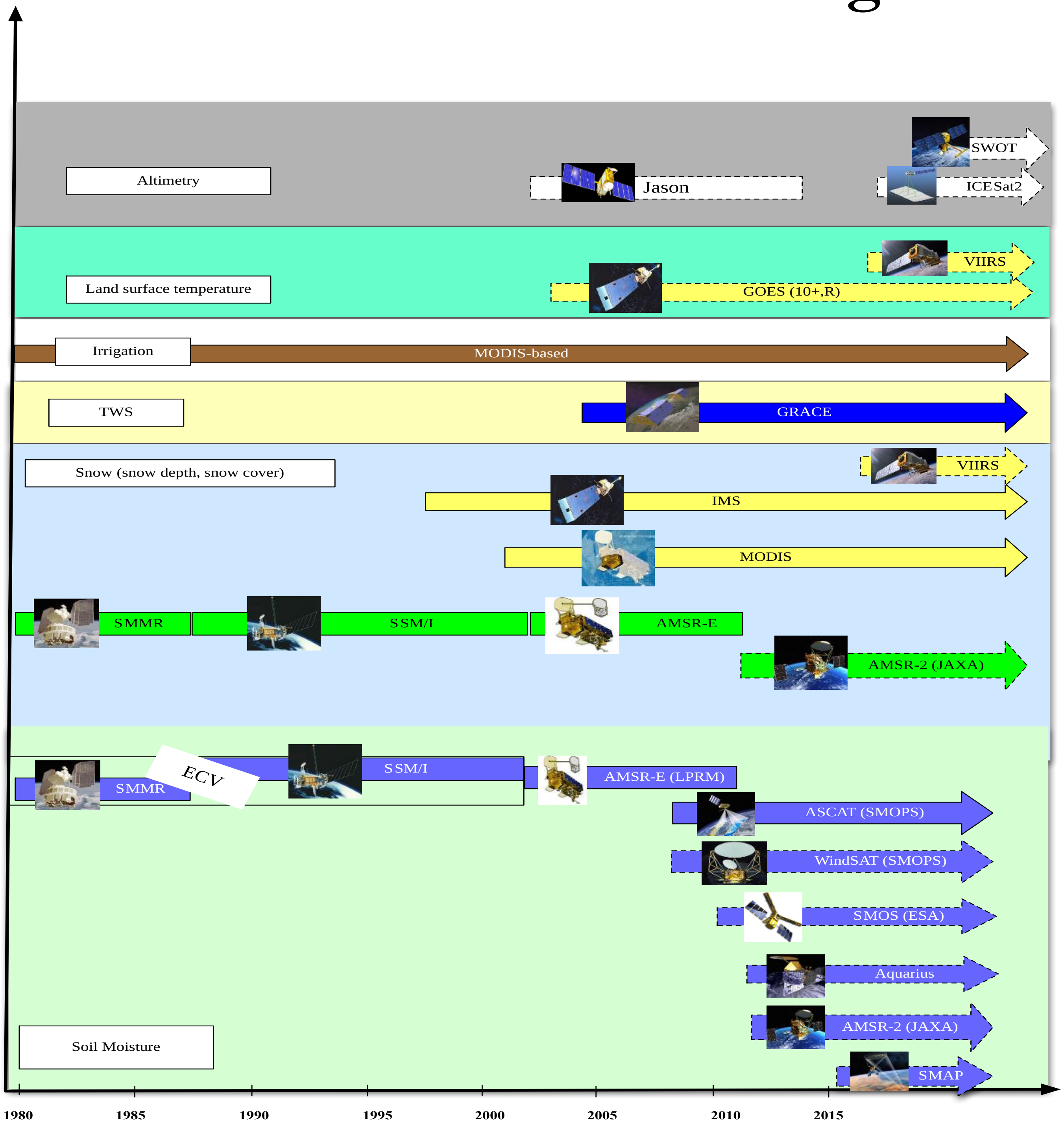
Kumar, S.V., R.H. Reichle, C.D. Peters-Lidard, R.D. Koster, X. Zhan, W.T. Crow, J.B. Eylander, P.R. Houser (2008), A Land Surface Data Assimilation Framework using the Land Information System: Description and Applications, *Adv. Wat. Res.*, 31, 1419-1432.

An Integrated Terrestrial Water Analysis System enabled by LIS



A unique analysis that concurrently employs a comprehensive set of remote sensing measurements to constrain terrestrial water budget terms in the NLDAS configuration, using LIS-DA capabilities.

NLDAS configuration



Model domain: Continental United States (CONUS) at 1/8th degree spatial resolution, including parts of Canada/Mexico (25-53° N; 125-67° W)

Forcing data: NLDAS-phase II (NLDAS2) meteorological forcing data.

Models: Noah LSM version 3.3, and CLSM Fortuna 2.5: a 60-year spin-up, followed by 34 years of simulation; streamflow simulations using HyMAP (Getirana et al. 2012)

Data assimilation method: 1-d Ensemble Kalman Filter (EnKF) and 3-d Ensemble Kalman Smoother (EnKS)

Time period: Jan 1, 1979 to 1 Jan 2013.

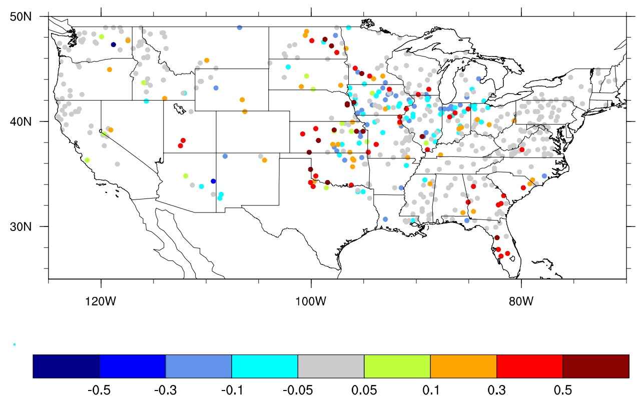
Boxes with solid lines represent products that are currently assimilated, dashed boxes represent products in pipeline

Assimilation of remotely sensed soil moisture measurements in NLDAS (Univariate assimilation)

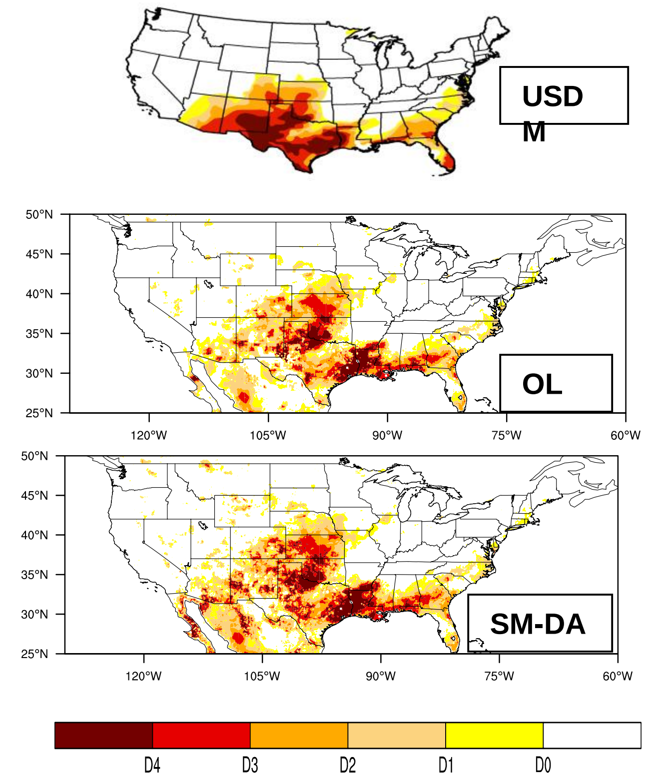
The impact of assimilating soil moisture retrievals from SMMR, SSMI, AMSR-E, ASCAT into the Noah LSM during a time period of 1979-2012.

Anomaly R	Open loop (no DA)	Soil moisture DA
Vs ARS CalVal (surface)	0.84 +/- 0.02	**0.86 +/- 0.02**
Vs SCAN (surface)	0.67 +/- 0.02	**0.67 +/- 0.02**
Vs SCAN (root zone)	0.60 +/- 0.02	**0.59 +/- 0.02**

Impact of soil moisture DA on soil moisture skills



Impact of soil moisture DA on streamflow skills (Warm colors indicate locations where DA provides improvement in streamflow NSE and cool colors indicate locations where DA leads to degradation in streamflow NSE)



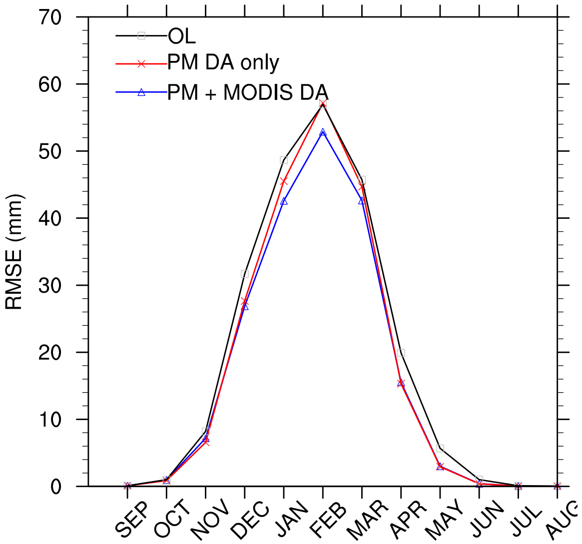
Impact of soil moisture DA on drought estimates (May 10-17, 2011).

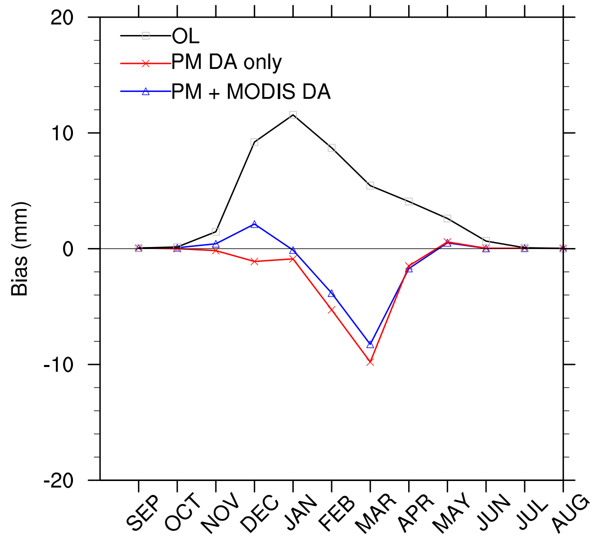
- Improvements in soil moisture fields are barely at the statistically significant levels
- Small improvements in streamflow
- Improvements in drought estimates at short time scales are seen from soil moisture DA

Kumar, S.V., C.D. Peters-Lidard, D. Mocko, R. Reichle, Y. Liu, K. Arsenault, Y. Xia, M. Ek, G. Riggs, B. Livneh, M. Cosh: 2014
Assimilation of remotely sensed soil moisture and snow depth retrievals for drought estimation. *Journal of Hydrometeorology*, 15, 2446-2469, doi: http://dx.doi.org/10.1175/JHM-D-13-0132.1

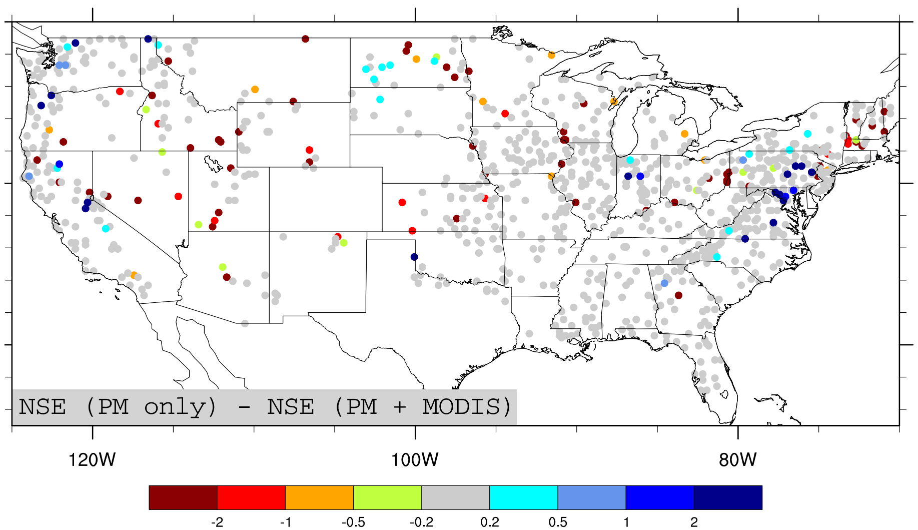
Assimilation of remotely sensed snow depth and snow cover measurements in the NLDAS (Univariate assimilation)

Quantify the added impact of using snow covered area (SCA) from MODIS during the assimilation of passive microwave snow depth observations.





Average seasonal cycle of RMSE and Bias for snow depth from the open loop (OL) and DA integrations

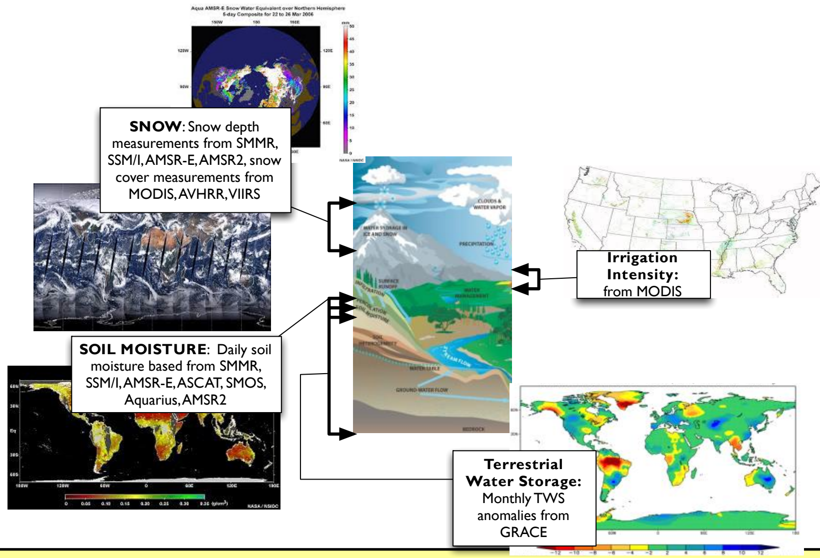


Differences in NSE of streamflow estimates from the use of MODIS SCA over passive microwave data alone

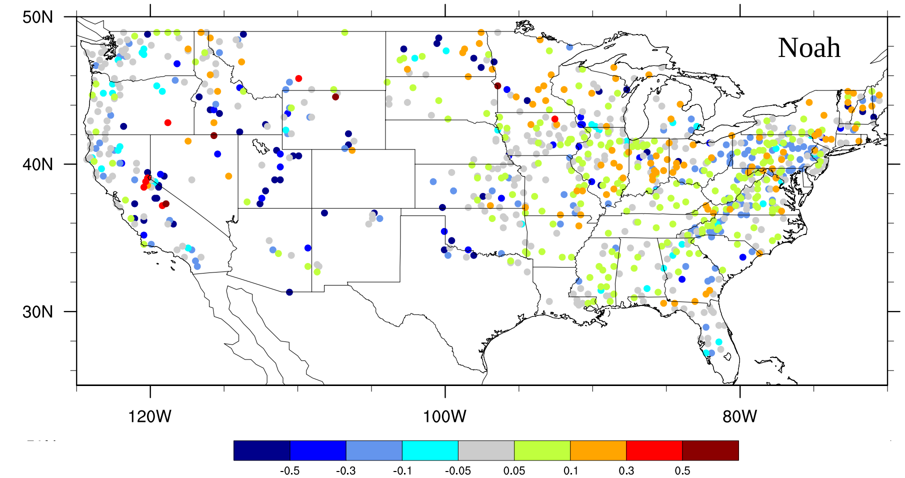
- The use of MODIS data provides systematic improvements in snow depth fields over the assimilation of passive microwave data alone.
- These improvements are translated to improvements in streamflow, especially in the western U.S.

Kumar, S.V., C.D. Peters-Lidard, K.R. Arsenault, A. Getirana, D. Mocko, Y. Liu: 2015
Quantifying the added value of snow cover area observations in passive microwave snow depth data assimilation
Journal of Hyrometeorology, in press, doi:10.1175/JHM-D-15-0021.1

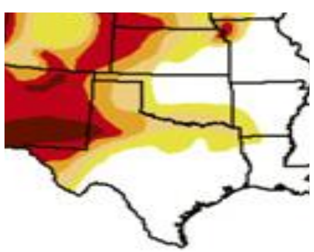
Multivariate assimilation of satellite-derived remote sensing datasets in the National Climate Assessment LDAS



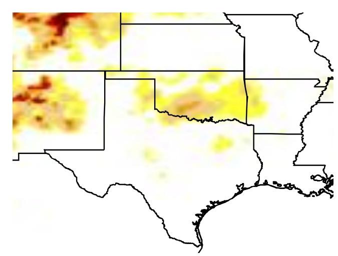
The concurrent, multivariate assimilation of various terrestrial hydrological datasets (soil moisture, snow depth, snow cover, terrestrial water storage, irrigation intensity) has been demonstrated for the NCA LDAS.



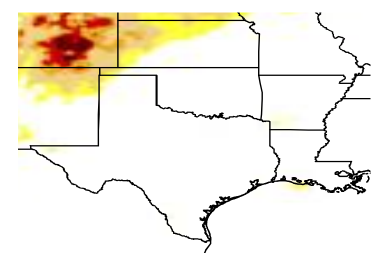
Multivariate assimilation of satellite remote sensing datasets are helpful in improving water budget components, including streamflow



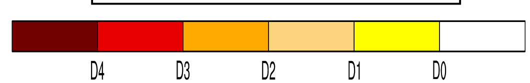
US drought monitor



LSM based drought estimate



LSM based drought estimate with data assimilation



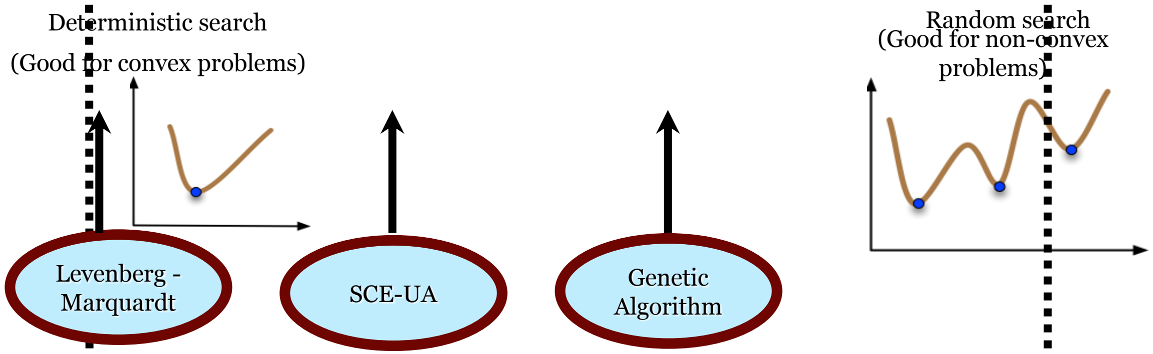
Impact of LDA on drought estimates (Sep, 2012).

Kumar et al. (2014):Assimilation of remotely sensed soil moisture and snow depth retrievals for drought estimation, J. Hydromet., 10.1175/JHM-D-13-0132.1
Kumar et al. (2016): Assimilation of gridded GRACE terrestrial water storage estimates in the North American Land Data Assimilation System, J. Hydromet., 10.1175/JHM-D-15-0157.1

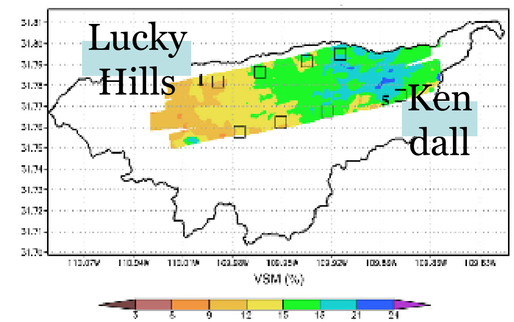
Optimization subsystem in LIS

- Data Assimilation is primarily a state estimation technique. It only “adjusts” model states, does not correct inherent model behavior

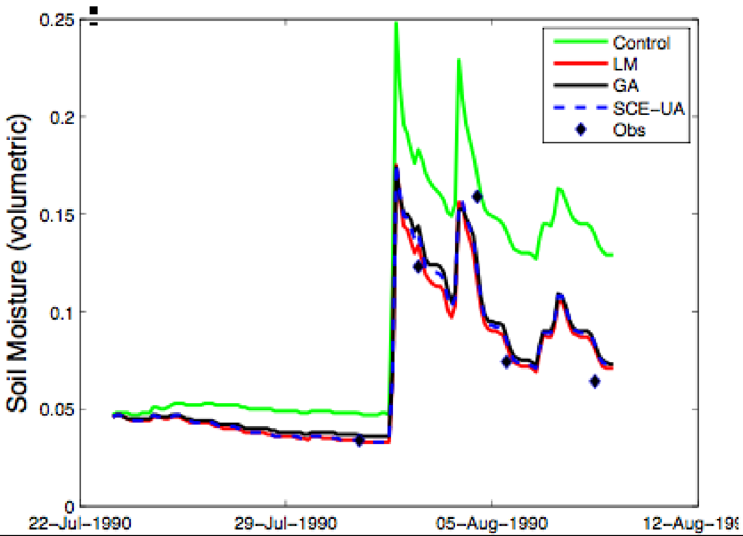
Use observational information to estimate model parameters; another way to use observations for informing models



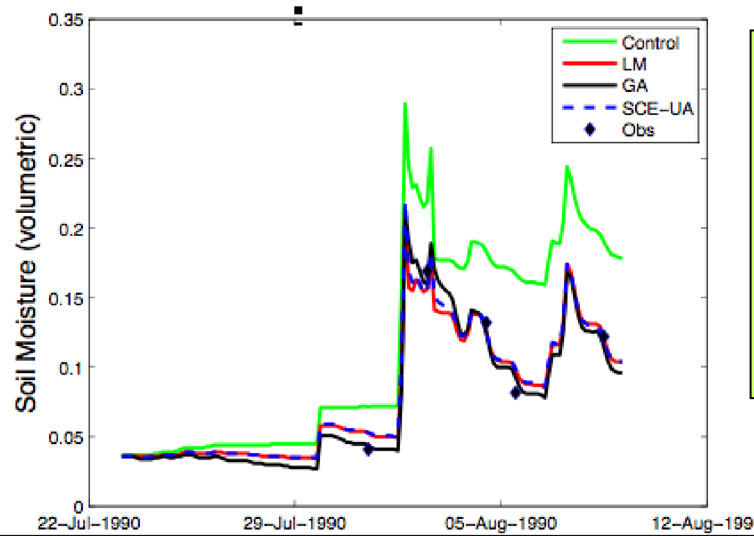
Case study from Santanello et al. (2007)



Site 1: Lucky Hills



Site 5: Kendall



Model parameters calibrated using passive (L-band) microwave remote sensing (using NASA’s push broom microwave radiometer - PBMR)

Kumar, S.V., R.H. Reichle, K.W. Harrison, C.D. Peters-Lidard, S. Yatheendradas, J.Santanello (2012), A comparison of methods for a priori bias correction in soil moisture data assimilation, *WRR*, 48(3),doi:10.1029/2010WR010261.

Uncertainty estimation (UE) subsystem in LIS

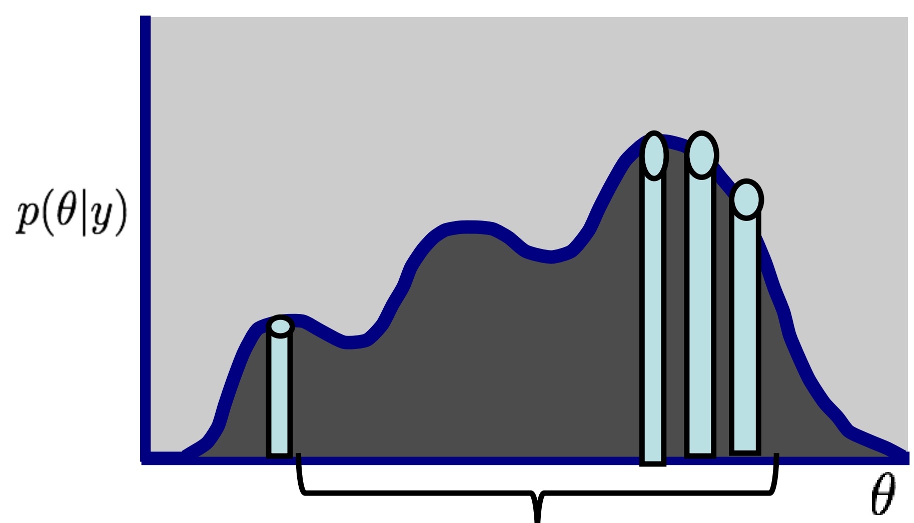
- Land surface model predictions are subject to uncertainties in model parameters, input forcing and model structure

- Posterior prediction – Uncertainty estimation incorporates different sources of uncertainty in reproducing observed behavior

  - Knowledge of uncertainty can help in the risk assessment for decision making (e.g. uncertainty in soil moisture predictions can be used in deciding irrigation practices).

- Preposterior analysis – Bayesian analysis can be used to investigate the value of data from proposed missions, suitable for OSSEs.

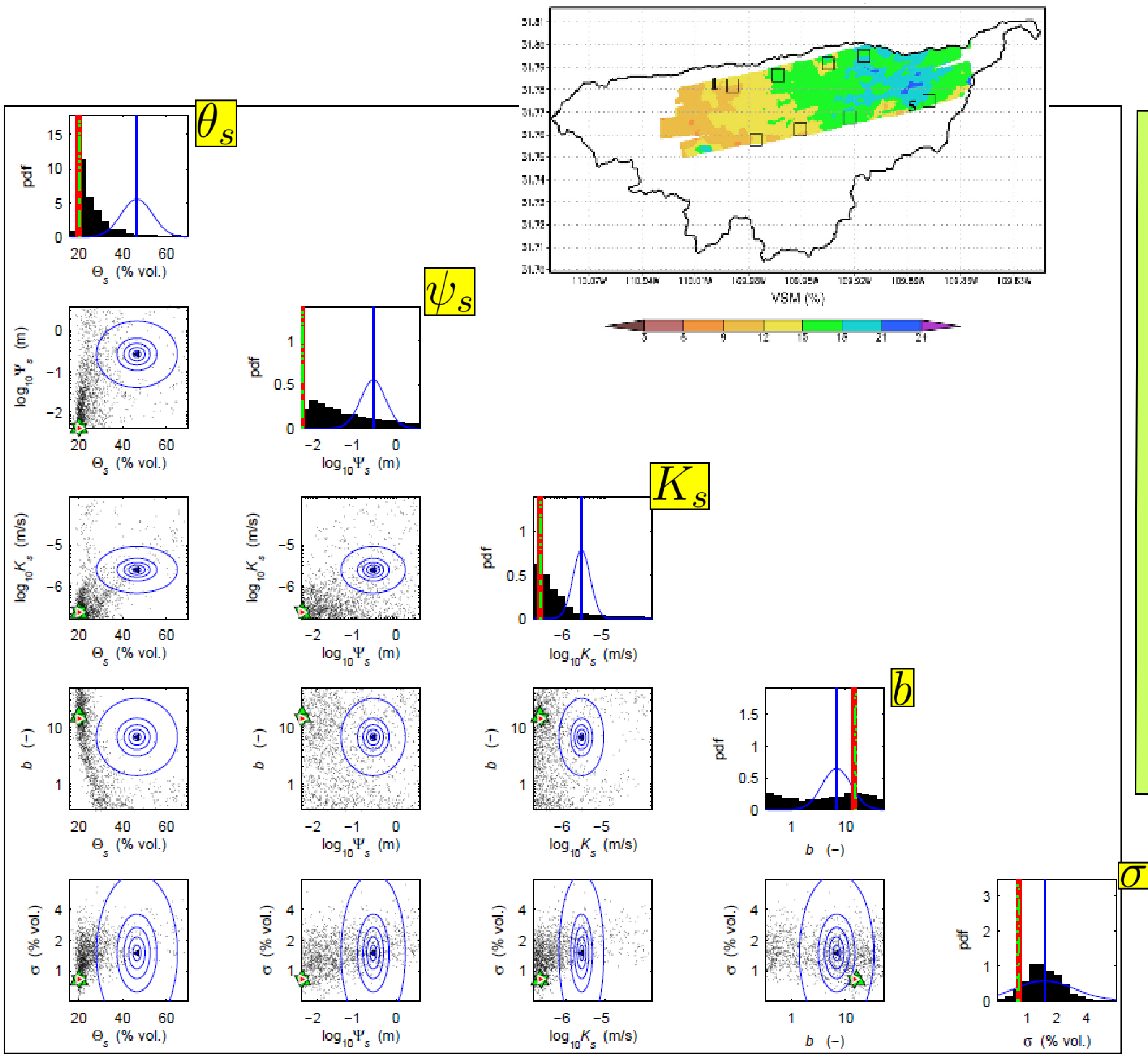
- A range of UE algorithms –
  - Monte Carlo propagation
  - Random Walk Markov Chain Monte Carlo (RW-MCMC)
  - Differential Evolution Monte Carlo (DEMC)
- MCMC algorithms revise input uncertainties based on information from observations



Harrison, K.E., S.V. Kumar, J.A. Santanello, C.D. Peters-Lidard (2012), Quantifying the change in soil moisture modeling uncertainty from remote sensing observations using Bayesian inference techniques, *WRR*, 48(11), 7489-7504.

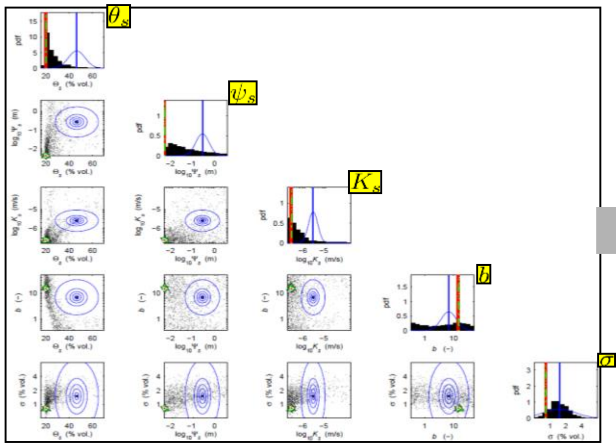
Posterior parameter distributions – DEMC

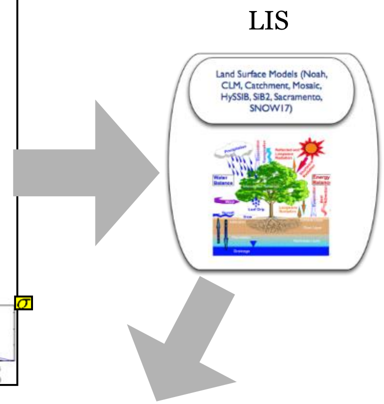
$p(\theta|y)$



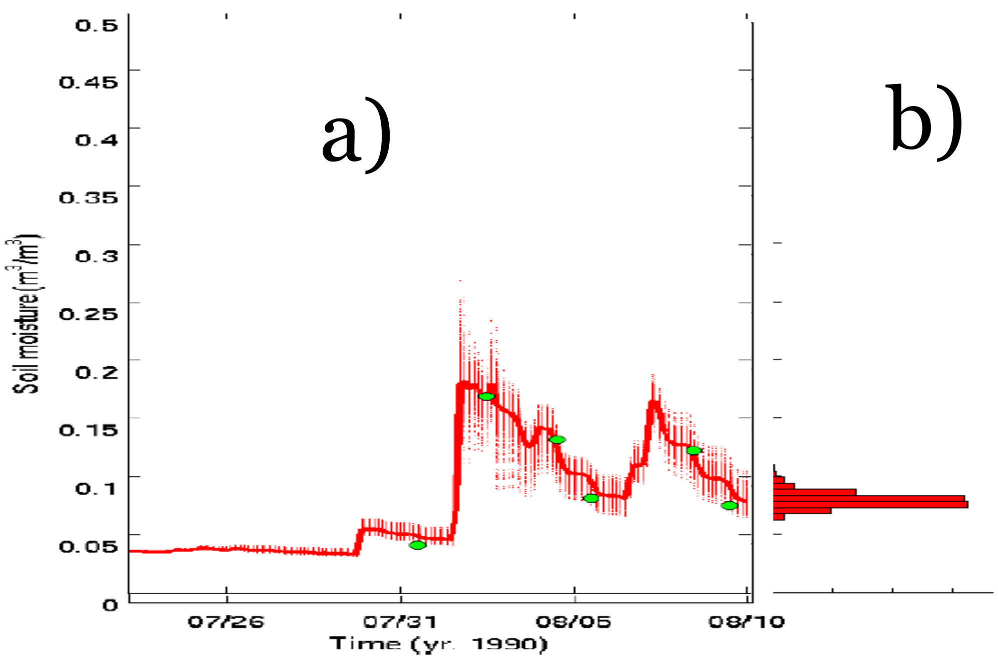
- The parameter distributions in the 2-d space shows the reduction in uncertainty after incorporating observational information
- Large shift in probability mass away from prior, lack of influence of the prior
- Distributions indicate cross-correlations between parameters
- "Best" fits ignore uncertainty

Probabilistic prediction





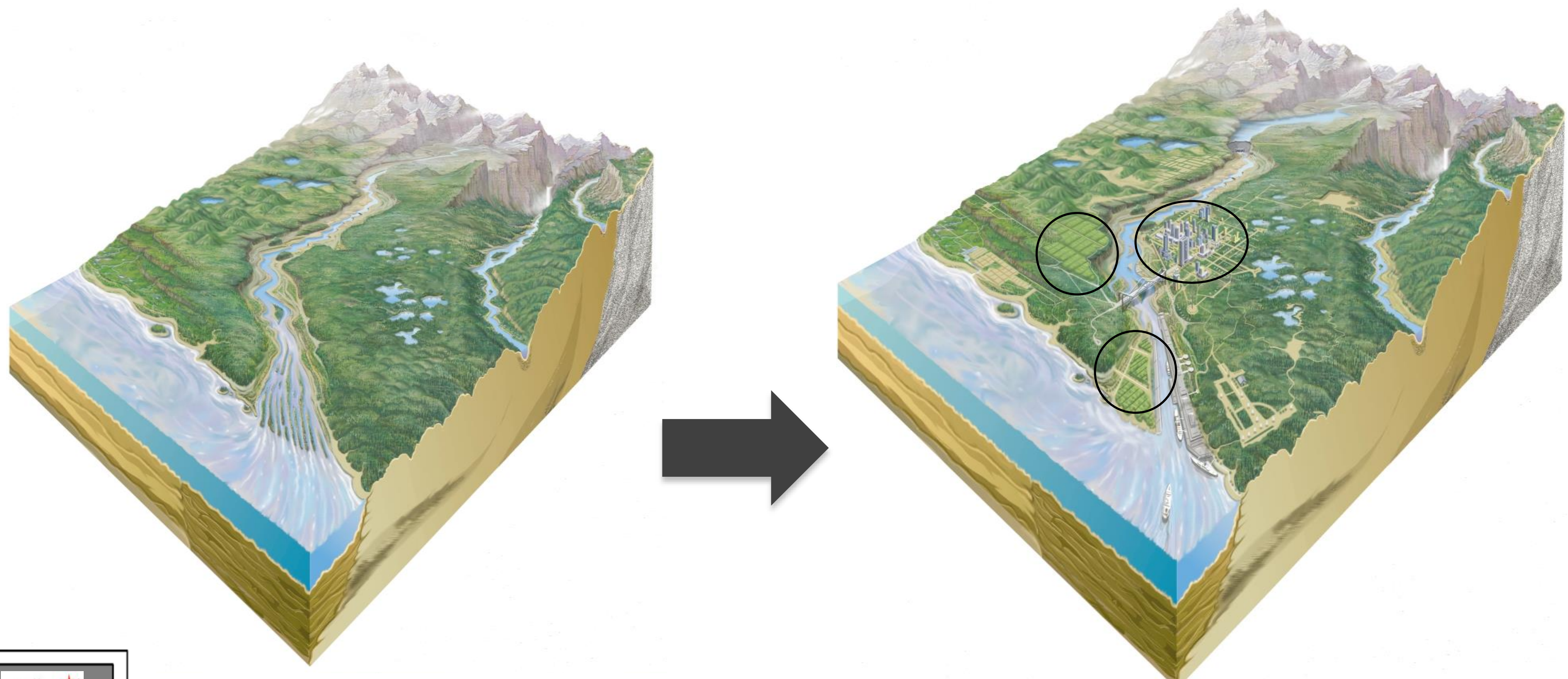
- Value of remote sensing = reduction in uncertainty
- Needed input to assessing value of proposed missions (basis of OSSEs)

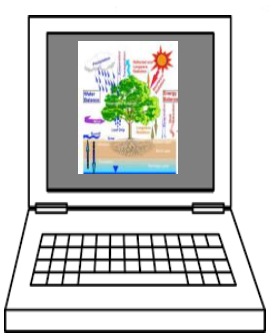


prior=blue (MC-SIM) posterior=red (DEMC)

a. The soil moisture time series with all sample fits (θ); curve is the median across fits.
b. The probabilistic forecast of soil moisture for the final time step

Human impacts from expansion of agriculture and infrastructure have significantly (>50%) transformed the natural features of the land surface





Land surface models : fairly utopian; hard to realistically represent subjective practices

Remote sensing: practical method to observe these ‘unmodeled’ features

Summary

- Land Data Assimilation Systems have been developed for central North America (NLDAS, NCA-LDAS), Africa (FLDAS) and the globe (GLDAS)
- The common goal of these projects is to integrate all relevant data in a physically consistent manner within sophisticated land surface models to produce optimal estimates of hydrological states (e.g. soil moisture, surface temperature) and fluxes (e.g. runoff, evapotranspiration)
- The Land Information System (LIS) is an efficient and configurable software that can be used to specify an instance of LDAS
- LDASs have been used for water availability applications including drought/flood monitoring, agricultural management, weather and climate initialization.